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Abstract. Computer-assisted automated exudate detection is crucial for large-scale screening of diabetic retinopathy (DR). The motivation of this work is robust and accurate detection of low contrast and isolated hard exudates using fundus imaging. Gabor filtering is first performed to enhance exudate visibility followed by Tsallis entropy thresholding. The obtained candidate exudate pixel map is useful for further removal of falsely detected candidates using sparse-based dictionary learning and classification. Two reconstructive dictionaries are learnt using the intensity, gradient, local energy, and transform domain features extracted from exudate and background patches of the training fundus images. Then, a sparse representation-based classifier separates the true exudate pixels from false positives using least reconstruction error. The proposed method is evaluated on the publicly available e-optha EX and standard DR database calibration level 1 (DIARETDB1) databases and high exudate detection performance is achieved. In the e-optha EX database, mean sensitivity of 85.80% and positive predictive value of 57.93% are found. For the DIARETDB1 database, an area under the curve of 0.954 is obtained. © 2017 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JMI.4.2.024002](https://doi.org/10.1117/1.JMI.4.2.024002)]

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1 Introduction

Diabetic retinopathy (DR) is the damage caused to the retina due to progression of diabetes.¹ If untreated, DR can cause partial or complete vision loss, which is irreversible. In 2014, the World Health Organization estimated that 9% of the global adult population suffered from diabetes.² DR causes the retinal vasculature to become delicate and ooze out fluids such as lipids, glucose, and blood onto the retinal surface. In the nonproliferative (initial) stage of DR, lesions like microaneurysms (swelling on the vessel endings), hemorrhages (blood leakage from the vessel endings), and exudates become evident.³ Exudates are settlements of proteins and retinal fluids from the blood vessels on the retinal surface.⁴ In the proliferative stage, new blood vessels grow abnormally (neovascularization) to improve blood circulation in the retina. Laser photocoagulation surgery is performed to reduce the rate of progression of the disease.¹ However, the treatment cannot cure the already damaged portions of the visual system. Therefore, early accurate detection and quantification of DR is very crucial to slow down the progression of the disease.

Computer-aided exudate detection is known to be a challenging problem since significant variation exists in their scale, shape, and location in fundus images. The resemblance in the intensity values of the optic disk and exudate regions makes the detection task further complicated. Various methods are available in literature for detecting exudates in DR affected fundus images. Sanchez et al.⁵ performed color normalization and contrast enhancement as a preprocessing step for removing uneven illumination in the fundus image. As feature extraction, the Frei–Chen operator is applied to obtain the exudate edges and Fisher's linear discriminant is used for exudate

classification. The method achieved a sensitivity value of 88% and mean false positive per image of 4.83 ± 4.64 on a database of 58 retinal images. In Ref. 6, the Gaussian mixture model is applied to model the histogram of the enhanced fundus image and dynamic thresholding is performed to obtain candidate exudates. An edge strength analysis is performed to remove cotton wool spots and other bright artifacts during postprocessing. The algorithm obtained the sensitivity of 90.2% and positive predictive value (PPV) of 96.8% using lesion level evaluation using a database of 80 retinal images.

Jaafar et al.⁷ proposed a two-stage methodology for detection and grading of hard exudates. A coarse level segmentation is initially performed based on the standard deviation and then region-based segmentation is performed to obtain the exudates regions. Yazid et al.⁸ applied a clustering-based approach for the segmentation of exudates. Fuzzy C-means clustering followed by edge detection and Ostu's thresholding is applied for detection of edges of exudates. Inverse surface thresholding is then considered to distinguish between hard and soft exudates. The method obtained a sensitivity of 98.2% and specificity of 97.4% on DIARETDB1 dataset and 90.2% of sensitivity and 99.2% specificity on National University Hospital of Malaysia dataset. Attempts have been made to detect diabetic macular edema (DME) by locating the presence of exudates in the proximity of macula. Giancardo et al.⁹ proposed a DME detection method by extracting various color- and wavelet-based features. Three different categories of classifiers, such as probabilistic (Naive Bayes classifier), geometric [support vector machine (SVM)], and tree based (random forest), are applied for DME classification. The algorithm is evaluated on a Hamilton Eye Institute macular edema dataset (HEI-MED), MESSIDOR, and DIARETDB1 databases.

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Deepak and Sivaswamy¹⁰ proposed a two-step methodology for detection of exudates and classification of DME using supervised learning. The severity level of DME is obtained using a rotational asymmetry measure. A morphology-based approach for exudate detection is presented in Refs. 11 and 12. A statistical atlas-based method is proposed by Ali et al.¹³ In this method, the lesions are detected by unwrapping the fundus image on the atlas co-ordinates and computing the distance from the mean atlas image. The method achieves an overall accuracy of 82.6%. Agurto et al.¹⁴ applied optimal thresholding on the instantaneous amplitude components extracted from the multiple frequency scales to generate candidate exudates. Several color-, texture-, and shape-based features are extracted to classify the presence or absence of exudates in the macula region.

Pereira et al.¹⁵ performed background removal, image normalization, and double thresholding to obtain the candidate image. Ant colony optimization technique is then explored for edge strength analysis of the candidate regions. The method is evaluated on the HEI-MED database and achieves an accuracy, sensitivity, and specificity of 97.85%, 80.82%, and 99.16%, respectively. Recently, an active contour-based approach for exudate detection is suggested in Ref. 16. Sparse dimensionality reduction of features obtained by texture analysis such as scale-invariant feature transform, histogram of oriented gradients, and local binary patterns is applied in Ref. 17. The SVM is then used to perform binary classification whether an image is normal or contains any artifacts, such as exudates and drusens. This method, however, does not provide any localized segmentation map of exudates in fundus images, which is considered a more challenging task.

In this paper, a methodology is formulated for accurate detection of hard exudates in fundus images, combining Tsallis entropy and sparse-based reconstructive dictionary learning and classification. While Tsallis entropy thresholding provides superior candidate exudate locations, sparse-based dictionary learning using training image patches and classification removes the false positives. The rest of the paper is organized as follows. Section 2 contains the details of the proposed method. In Sec. 3, experimental results and discussion are provided after evaluation with the e-optha EX and the DIARETDB1 databases. Section 4 concludes the paper.

2 Proposed Methodology

Green channel image (I_G) is considered for various steps of the proposed method because it provides better contrast in comparison to other channels.¹⁵ The block diagram of the proposed method is given in Fig. 1. As preprocessing, Gabor filtering of I_G is performed to enhance the visibility of exudate regions.

2.1 Gabor Filtering

Gabor filters are orientation-specific filters that provide strong response for structures in an image oriented in the direction of the filter. Mathematically, the 2-D Gabor function is defined as follows:

$$g_\theta = \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \exp\left[\frac{j\pi}{\lambda}(x \cos \theta + y \sin \theta)\right], \quad (1)$$

where θ is the filter orientation, λ is the wavelength of the filter, and σ is the scale of the filter.¹⁸ Figure 2 shows the Gabor filters at different orientations for a particular wavelength ($\lambda = 6$). Gabor filters find successful applications in texture analysis,¹⁹ iris segmentation,²⁰ fingerprint enhancement,²¹ and motion tracking.²² Exudates in fundus images have neither very sharp edges nor definite orientations. Therefore, the Gabor filters at experimentally chosen orientations of $\{0, 45, 90, 135 \text{ deg}\}$ are applied to I_G . Some of the properties of Gabor filters that make them suitable for exudate enhancement are the invariance to luminance, translation, and orientation of the image.²³ The filtering output is summed to get an image that enhances the exudates in comparison to other retinal structures (blood vessels, artifacts; Fig. 3). The encircled regions in Figs. 3(a)–3(d) indicate the location of the exudates in both the fundus and enhanced images. The computation of the Gabor filtered image (I_{Gabor}) is given in the following equation:

$$I_{\text{Gabor}} = \sum_{\theta} I_G * g_\theta. \quad (2)$$

2.2 Tsallis Entropy Thresholding

Tsallis entropy is associated with pseudoadditivity property, which assumes that the foreground and background are not

Fig. 1 Block diagram of the proposed method.

Fig. 2 Gabor filters at different orientations of {0 deg, 45 deg, 90 deg, 135 deg}.

statistically independent.^{24–26} Due to the varying edge strengths of exudates and low contrast of the fundus images, it is essential to consider an interaction term between the object (exudates) and background, which is achieved by Tsallis entropy-based thresholding. Given a probability distribution (p) of a system having (N) states, the Tsallis entropy is given as follows:

$$H_{\text{Tsallis}} = \frac{1 - \sum_{i=1}^N p_i^q}{q - 1}, \quad (3)$$

where q is known as the entropic index, which controls the degree of inter-relation between object and background.

The pseudoadditivity property of Tsallis entropy between the object (O) and background (B) is given as follows:

$$H(O + B) = H_{\text{Tsallis}}(O) + H_{\text{Tsallis}}(B) + (1 - q)H_{\text{Tsallis}}(O)H_{\text{Tsallis}}(B). \quad (4)$$

The gray level co-occurrence matrix is computed as

$$C = [l_{ij}]_{L \times L}, \quad i, j = 0, \dots, L, \quad (5)$$

where l_{ij} is the position operator and taken as one pixel immediately to the right²⁷ and L is the maximum gray level of the image.

Fig. 4 Quadrants of co-occurrence matrix.

Mathematically, l_{ij} is given as follows:

$$l_{ij} = \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} \Delta, \quad (6)$$

where $m \times n$ is the size of the image and

$$\Delta = \begin{cases} 1 & \text{if } I(p, q) = i \text{ \& } I(p, q + 1) = j \\ 0 & \text{otherwise} \end{cases}. \quad (7)$$

The elements of normalized co-occurrence matrix at gray levels i and j are given as follows:

$$P_{ij} = \frac{l_{ij}}{\sum_{i=1}^L \sum_{j=1}^L l_{ij}}. \quad (8)$$

In order to obtain the optimum threshold T_f , an initial threshold T is set to 0 and varied incrementally up to L . The threshold T divides the co-occurrence matrix into four quadrants as given in Fig. 4.

Quadrants 1 and 4 contain information from the background and object, respectively, whereas quadrants 3 and 4 contain

Fig. 3 (a and b) Fundus images, (c and d) Gabor-filtered enhanced image, and (e and f) Tsallis entropy thresholded image.

information about edges and noises.²⁸ As we are interested in the object-background segmentation, only quadrants 1 and 4 are considered for further processing.

The normalized probabilities of the first and fourth quadrant are given as follows:

$$Q_{ij}^1 = \frac{P_{ij}}{\sum_{i=0}^T \sum_{j=0}^T P_{ij}}, \quad (9)$$

$$Q_{ij}^4 = \frac{P_{ij}}{\sum_{i=T+1}^L \sum_{j=T+1}^L P_{ij}}. \quad (10)$$

The Tsallis entropy of the object and background is given as follows:

$$H_q^4(T) = \frac{1 - \sum_{i=T+1}^L \sum_{j=T+1}^L \{Q_{ij}^4\}^q}{q - 1}, \quad (11)$$

$$H_q^1(T) = \frac{1 - \sum_{i=0}^T \sum_{j=0}^T \{Q_{ij}^1\}^q}{q - 1}. \quad (12)$$

The optimum threshold for segmentation of exudates from the background is obtained as follows:

$$T_f = \arg \max_T \{H_q^1(T) + H_q^4(T) + (1 - q)H_q^1(T)H_q^4(T)\}. \quad (13)$$

Tsallis entropy thresholding is applied to the normalized Gabor filtered output (I_{Gabor}) and the segmented output obtained (I_{Tsallis}) is shown in Figs. 3(e)–3(f). I_{Gabor} is normalized in gray-scale because the accumulation of the filtered output with different orientations of the Gabor filter may exceed the grayscale dynamic range. It can be observed that some of the nonexudate bright artifacts and the optic disk have also been detected as exudates. The optic disk is localized and removed using an existing algorithm described in Ref. 29. The falsely detected bright artifacts are removed by designing the sparse representation classifier that utilizes several patch-based features.

2.3 Feature Extraction

In this step, various features based on intensity, gradient, local energy, and transform coefficients are extracted from $(n \times n)$ image patches to learn two reconstructive dictionaries for classification of exudates and background. Prior to feature extraction, the blood vessel structures are removed using inpainting to aid in reducing false positives.^{30,31}

- **Intensity features:** As exudates are relatively bright in comparison to the background, the intensity values in the *RGB* and *YCbCr* plane provide distinguishing features for classification. A total of $(n^2 + 5)$ features are extracted: the intensity values of $n \times n$ patch of the green channel inpainted image, the mean of *R*, *G*, *B*, *Cb*, and *Cr* channels in the inpainted image.
- **Gradient features:** Image gradient provides information about directional intensity changes in the green channel inpainted image. Therefore, the mean of *x* and *y* directional gradients, the mean of gradient magnitude and direction are used as features:

$$g_x = \frac{dI}{dx}, \quad (14)$$

$$g_y = \frac{dI}{dy}, \quad (15)$$

$$g = \sqrt{g_x^2 + g_y^2}, \quad (16)$$

$$\theta = \tan^{-1} \left(\frac{g_y}{g_x} \right), \quad (17)$$

where g_x is the gradient in *x*-direction, g_y is the gradient in *y*-direction, g is the total gradient magnitude, and θ is the gradient angle.

- **Local energy feature:** Local energy feature is important for obtaining low contrast and isolated (small dots) exudates, which do not contain very sharp and prominent edges. Local energy could detect features that are invariant to illumination, contrast, and magnification.³² The local energy computed from I_{Gabor} is given by

$$E(x, y) = \sqrt{I_{\text{Gabor}}^2(x, y) + \tilde{H}^2(x, y)}, \quad (18)$$

$$\tilde{H}(x, y) = I_{\text{Gabor}}(x, y) * \frac{1}{\pi^2 xy}, \quad (19)$$

where $E(x, y)$ is the local energy and $\tilde{H}(x, y)$ is the Hilbert transform of I_{Gabor} . In the proposed method, the local energy is efficiently computed by using the phase congruency function.³² In Fig. 5, the local energy magnitude at the exudate pixels is observed to be very high. Thus, the mean local energy in both exudate and nonexudate patches is used as a discriminative feature.

- **Transform domain features:** 2-D discrete cosine transform (DCT) coefficients²⁷ computed from the inpainted image patches (green channel) are treated as features to capture the frequency information contained in the exudates:

$$C(u, v) = \left(\frac{2}{n} \right)^{1/2} \left(\frac{2}{n} \right)^{1/2} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \Lambda(i) \Lambda(j) \cos \left[\frac{\pi u}{2n} (2i + 1) \right] \cos \left[\frac{\pi v}{2n} (2j + 1) \right] p(i, j), \quad (20)$$

where $p(i, j)$ represents the pixels of the image patch, n is the size of the patch, $C(u, v)$ is the 2-D DCT of $p(i, j)$ and

$$\Lambda(i) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } i = 0 \\ 1 & \text{otherwise} \end{cases}. \quad (21)$$

The extracted feature vector (f) and its components are summarized in Table 1. The feature index (first column) indicates the succession of individual features in the final feature vector and the second column provides their brief description.

Fig. 5 (a) Gabor filtered image and (b) local energy map.

Table 1 Summary of the extracted features.

Feature index	Feature description
1	Intensity values of the $n \times n$ image patch
2 to 4	Mean RGB values of the patch
5 and 6	Mean Cb , Cr values of the patch
7 and 8	Mean gradient values in the x - and y -directions
9 and 10	Mean gradient magnitude and angle
11	Mean local energy of the patch
12	DCT coefficients of the patch

2.4 Sparse-Based Reconstructive Dictionary Learning and Classification

2.4.1 Sparse representation

Sparse representation is a recent technique to represent signals in a compact form as linear combination of dictionary atoms.³³ Given an input sample X and dictionary $D = \{D_1, D_2, \dots, D_N\}$, where $D_1 \dots D_N$ are the atoms of the dictionary D , the motivation of sparse coding is to express the input sample X as

$$X = D\alpha, \quad (22)$$

where α is a sparse vector. The solution to the above problem is not unique; therefore, a constraint is put on the choice of α . The optimum sparse vector $\hat{\alpha}$ is given as

$$\hat{\alpha} = \operatorname{argmin} \|\alpha\|_0, \quad \text{subject to } X = D\alpha, \quad (23)$$

where $\|\alpha\|_0$ is the l_0 norm of α . However, the solution to the above minimization problem is NP-hard.³³ Therefore, l_0 norm is replaced by l_1 norm, which makes the minimization in [Eq. (23)] a convex problem:

$$\hat{\alpha} = \operatorname{argmin} \|\alpha\|_1 \quad \text{subject to } \|D\alpha - X\|_2 < \xi, \quad (24)$$

where ξ is the bounded error. Equation (24) can be solved by greedy algorithms, such as matching pursuit and orthogonal matching pursuit (OMP).³⁴

2.4.2 Dictionary learning

A reconstructive dictionary has the ability to reconstruct the signal with low reconstruction error and less complexity. During reconstructive dictionary learning, both the sparse vector and the dictionary atoms are optimized using the following equation:

$$[D\alpha] = \operatorname{argmin}_{D,\alpha} \|X - D\alpha\|_2, \quad \|\alpha\|_0 < Z, \quad (25)$$

where Z is the sparsity factor. The above optimization is performed using the K-SVD algorithm.³⁵ A number of $n \times n$ training patches from the exudate and background regions are obtained and the feature vectors are computed. Using Eq. (25), two reconstructive dictionaries, such as exudate dictionary (D_{ex}) and nonexudate dictionary ($D_{\text{non-ex}}$), are learnt separately using the corresponding features.

2.4.3 Classification

In order to eliminate falsely detected exudate pixels, a $n \times n$ test patch is considered around each candidate exudate pixel (CEP) in (I_{Tsallis}) followed by the feature vector extraction (f). The OMP algorithm³⁴ then reconstructs the optimum sparse vectors α_{ex} and $\alpha_{\text{non-ex}}$ representing f using the dictionaries (D_{ex}) and ($D_{\text{non-ex}}$), respectively. The input candidate pixel belongs to the class that generates less error in representation. The residual error in representing the input patch is given as follows:

$$r_{\text{ex}} = \|f - D_{\text{ex}}\alpha_{\text{ex}}\|_2, \quad (26)$$

$$r_{\text{non-ex}} = \|f - D_{\text{non-ex}}\alpha_{\text{non-ex}}\|_2, \quad (27)$$

where r_{ex} and $r_{\text{non-ex}}$ are the residual errors for the respective classes.

The classification is given by the following equation:

$$\text{CEP} = \begin{cases} \text{exudate} & \text{if } r_{\text{ex}} \leq r_{\text{non-ex}} \\ \text{background} & \text{otherwise} \end{cases}. \quad (28)$$

The classification output for the test images is shown in Figs. 6(a)–6(b). A pseudocode for the sparse representation-based classification is given in Fig. 7.

2.5 Region Growing

The detected exudate pixels are now considered as seeds to obtain the accurate exudate region map. Region growing²⁷ is an effective technique, where initial seed pixels are chosen and compared with the neighboring pixels depending on the intensity based similarity criterion:

$$\text{Similarity criterion: } |a - \text{mean}(\text{CC})| \leq \eta, \quad (29)$$

where a is the intensity of the pixel to be added to CC, mean (CC) is the mean intensity value of the region CC, and η is the threshold. If the similarity criterion is satisfied by the neighbor, then it is added to the region. The output of the region growing operation is shown in Figs. 6(c)–6(d).

Fig. 6 (a and b) Result from the sparse representation classifier and (c and d) region growing output.

```

ClassifiedOut = 0
For each foreground pixel  $I_{Tsallis}(i, j)$  in  $I_{Tsallis}$ 
    • Take a  $n \times n$  patch around the foreground pixel  $I_{Tsallis}(i, j)$ 
    • Compute the feature vector ( $f$ ) of the patch
    • Find the sparse vectors using dictionaries  $D_{ex}$ ,  $D_{non-ex}$  and  $f$  as
         $\alpha_{ex} = OMP(D_{ex}, f)$ 
         $\alpha_{non-ex} = OMP(D_{non-ex}, f)$ 
    • Compute the reconstruction error
         $r_{ex} = \|f - D_{ex}\alpha_{ex}\|_2$ 
         $r_{non-ex} = \|f - D_{non-ex}\alpha_{non-ex}\|_2$ 
    • If  $r_{ex} \leq r_{non-ex}$ 
        ClassifiedOut( $i, j$ ) = 1
    End If
End For

```

Fig. 7 Pseudocode for sparse-based classification.

3 Experimental Results and Discussion

The exudate detection performance of the proposed method is demonstrated on two publicly available databases: e-ophtha EX¹¹ and the DIARETDB1.³⁶ The e-ophtha EX database contains 47 images with exudates and 35 images with no lesions. The database provides precise annotations of exudates at pixel level toward accurate evaluation of newly proposed methods. The DIARETDB1 contains 89 color fundus images out of which 84 images contain at least a mild sign of DR and 5 images with no sign of DR. Approximate annotations are available representing the location of exudates in the fundus images by four ophthalmologists. Our proposed method has been evaluated using all images on the basis of evaluation techniques originally suggested with the corresponding databases.^{11,36} For the e-ophtha database, a connected component analysis of the segmented output and ground truth is found for evaluation.¹¹ Sensitivity and PPV are then used as the performance measures:

$$\text{Sensitivity} = \frac{TP}{TP + FN}, \quad (30)$$

$$\text{PPV} = \frac{TP}{TP + FP}, \quad (31)$$

where TP is the true-positive count, FN is the false-negative count, and FP is the false-positive count. For the DIARETDB1 database, the evaluation strategy presented in Ref. 36 has been adopted. The ROC curve and the area under the ROC curve (AUC) are obtained as the performance measures.

The images are first resized to 512×512 pixels for fast computation. Different parameter values, which are consistent for all images, are experimentally decided to achieve optimum performance. During Gabor filtering, the wavelength factor is experimentally chosen as $\lambda = 6$. For sparse-based reconstructive dictionary learning (D_{ex}), the features from 8000 image patches are extracted from the exudate regions. Various patch sizes are experimentally tested and 11×11 pixels size is chosen as it yields better performance than others. A 252-dimensional feature vector is extracted from each image patch. A similar approach for the background region is followed for learning D_{non-ex} . The image patches are collected from 25 training images, which are selected randomly from the e-ophtha EX database. The same dictionaries are used for exudate detection in all DIARETDB1 database images. In the classification stage, a sparsity factor of $Z = 6$ is used for the test patch reconstruction. In region growing implementation, the threshold η for similarity criterion is chosen as 5.

For the e-ophtha EX database, dictionaries of different sizes have been experimented with, as shown in Table 2. It is found that the dictionary size of $K = 400$ provides good performance giving good sensitivity at an acceptable PPV. Though there should be a linear relationship between dictionary size and system performance, practically, it is not observed for exudate segmentation. The retinal structures are highly variable and do not have prominent and unified features for an ensemble of fundus images. Therefore, with increase of dictionary size, overfitting of the system occurs resulting in several misclassifications. The variation of mean sensitivity and PPV values with entropic index q is shown in Table 3.

It can be seen that the sensitivity increases indicating better exudate segmentation when the interaction between the object and background is high (small values of q). High interaction is

Table 2 Sensitivity and PPV at different dictionary sizes (K) for e-ophtha EX database.

Dictionary size (K)	Mean sensitivity	Mean PPV
100	63.35	53.34
200	65.77	73.11
300	72.54	56.21
400	85.80	57.93
500	77.92	55.01
600	81.88	67.92

The values in bold indicate the values finally used in the algorithm after experimentation with different parameter values.

Table 3 Sensitivity and PPV at different entropic index for e-optha EX database.

Entropic index (q)	Mean sensitivity	Mean PPV
0.1	86.80	54.78
0.2	86.56	54.68
0.3	86.42	54.45
0.4	86.22	55.12
0.5	86.01	55.76
0.6	85.95	56.23
0.7	84.92	56.89
0.8	85.80	57.93
0.9	84.54	57.88
1.0	89.98	25.78

Fig. 9 ROC curve for DIARETDB1 database at different entropic index.**Table 4** AUC for DIARETDB1 database.

Entropic index (q)	AUC
0.1	0.936
0.2	0.937
0.3	0.941
0.4	0.947
0.5	0.950
0.6	0.952
0.7	0.953
0.8	0.954
0.9	0.958
1.0	0.960

Fig. 8 (a) Mean sensitivity and (b) PPV values at different sparsity factor and entropic index for e-optha EX database.**Table 5** Performance comparison in e-optha EX database.

Method	Sensitivity (%)	PPV (%)
Zhang et al. ¹¹	83	49
Proposed method	85.80	57.93

Table 6 Performance comparison in DIARETDB1 database.

Method	AUC
Zhang et al. ¹¹	0.950
Giancardo et al. ⁹	0.930
Proposed method	0.954

Fig. 10 Fundus image (first column), Gabor-filtered image (second column), Tsallis entropy thresholded image (third column), classification output (fourth column), region growing output (fifth column).

required because the observed contrast between the exudates and background in the fundus images is low. It is the opposite for the PPV values; when more candidates are detected as probable exudates, the false-positive rate increases. Therefore, a

tradeoff has to be done between the entropic index (q), sensitivity, and PPV values. For q value of 0.8, both sensitivity and PPV values are observed to be optimum for the database. The mean sensitivity and PPV values at a different sparsity

factor (Z) and entropic index (q) are shown in Fig. 8. With the increase in sparsity factor, the detection rate increases as better representation of the test patch can be obtained with more numbers of dictionary atoms. However, the increase in sensitivity is penalized by a reduction in the PPV values.

The proposed sparse residual error-based classification system generates a binary output (yes/no) at each pixel of the test image. Since it is necessary to vary a threshold during classification to draw the ROC curves, it is difficult to plot in the e-optha EX database (with pixel level ground truth) using our proposed method. However, in the case of the DIARETDB1 database, even though we obtain binary classification output, the annotations provided by the ophthalmologists have different confidence levels (<50%, >50%, 100%), representing the certainty of the decision that the marked region is diseased.³⁶ By varying the confidence factors, different ground truth maps are generated. Then, various sensitivity and specificity values are computed for the confidence factors and hence, the ROC curve can be drawn.³⁶

For the DIARETDB1 database, the ROC plot for different q values is shown in Fig. 9. AUC is a measure of the performance of a classifier and ROC curve with higher AUC indicates for a better classifier. The comparison of AUC values for different entropic indices is given in Table 4. Significant variation is not observed here as the mean AUC is found as 0.9488 with standard deviation of 0.0084. However, as the interaction between the object (exudates) and background (other retinal structures) increases (with increasing q), the AUC follows an increasing trend implying improved performance of the system.

The proposed method is compared with the existing method¹¹ for the e-optha EX database. The method generates a binary exudate map unlike the probabilistic one used in Ref. 11. Thus, the results obtained at a threshold value of 0 in Ref. 11 are used for comparison in Table 5. In Table 6, the proposed method's performance for the DIARETDB1 database is compared with the existing methods.^{9,11} Some image-based results of the entire exudate detection process in both databases are given in Fig. 10. The proposed method requires 8.5 s on average to compute the exudate location map from a given fundus image using a general desktop computer (i5 8GB RAM, MATLAB environment). To compare, the required computational time is 9 s on a conventional computer for the previous method in Ref. 11, while the total time to diagnose an image is 9.3 s for the previous method in Ref. 9.

4 Conclusion

In this paper, an automated exudate detection method is proposed to be useful for mass screening of DR. The method initially demonstrates that Gabor filtering with a specific wavelength and different angular orientations enhances the exudate visibility in fundus images. The nonextensive property of Tsallis entropy makes the thresholding suitable for detection of candidate exudate regions. Also, the rate of interaction between the object and background entropy can be varied to obtain a tradeoff between the entropic index and detection rate. Various intensity, gradient, local energy, and transform domain-based patch features are extracted to learn the sparse reconstructive dictionaries. A reconstruction error-based classification is performed to get the accurately segmented exudate region map. The proposed method is evaluated on publicly available e-optha EX and DIARETDB1 databases with high exudate detection performance.

Disclosures

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